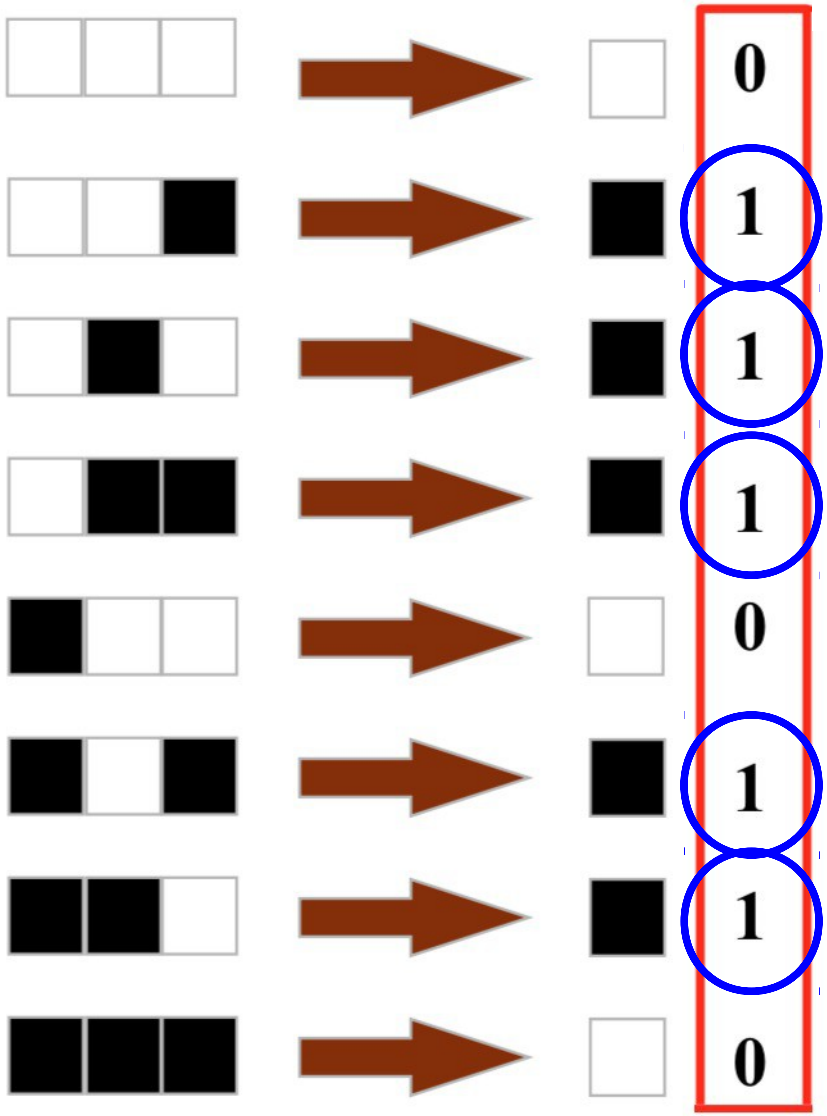
Langton's λ Parameter



ECA Rule 110

$\lambda = 5/8 = 0.625$

Langton's λ Parameter

- k = number of possible cell states
- Designate one state as the “quiescent” or “dead” state

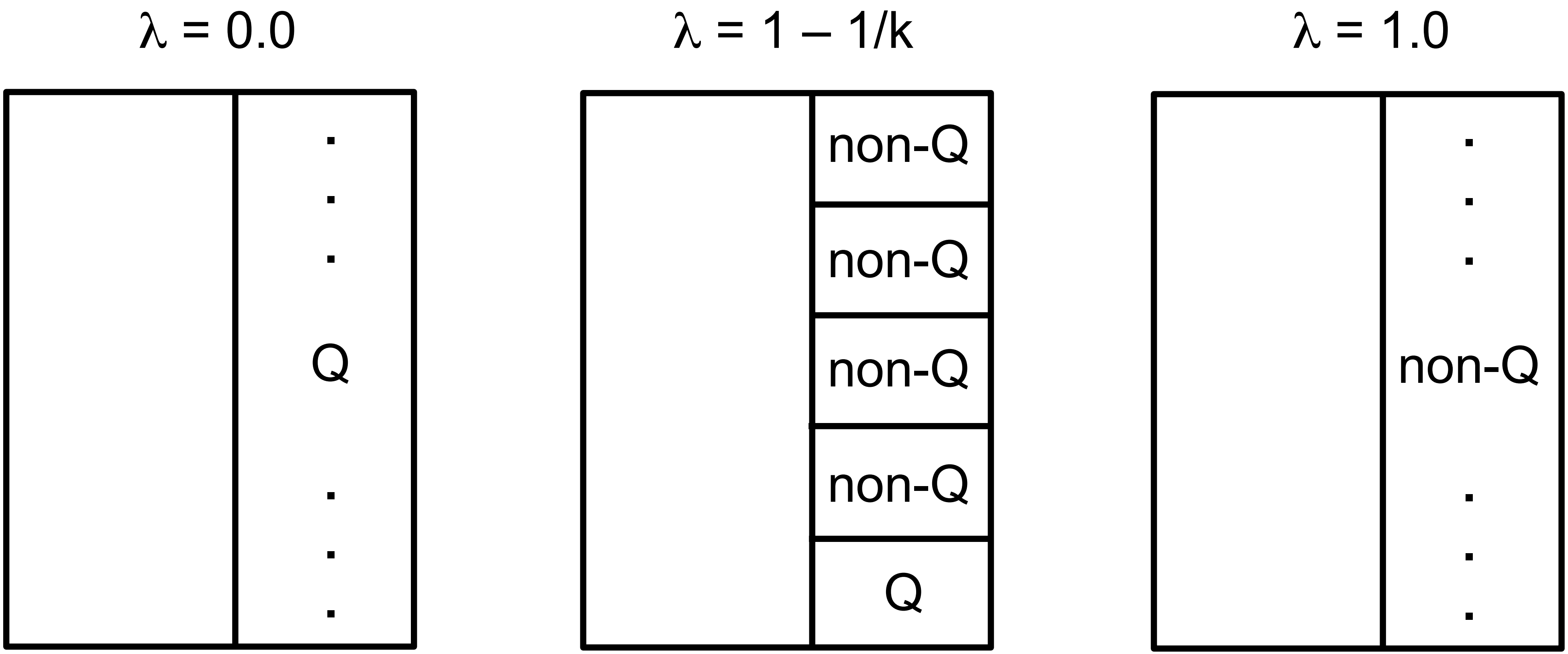
- N = total number of rules in the rule table
- q = # of rules that map to the quiescent state
- N – q = # of rules that map to non-quiescent states

- λ = fraction of non-quiescent states in the rule table

  = $(N - q) / N$

  = $1 - q/N$

Langton's λ Parameter

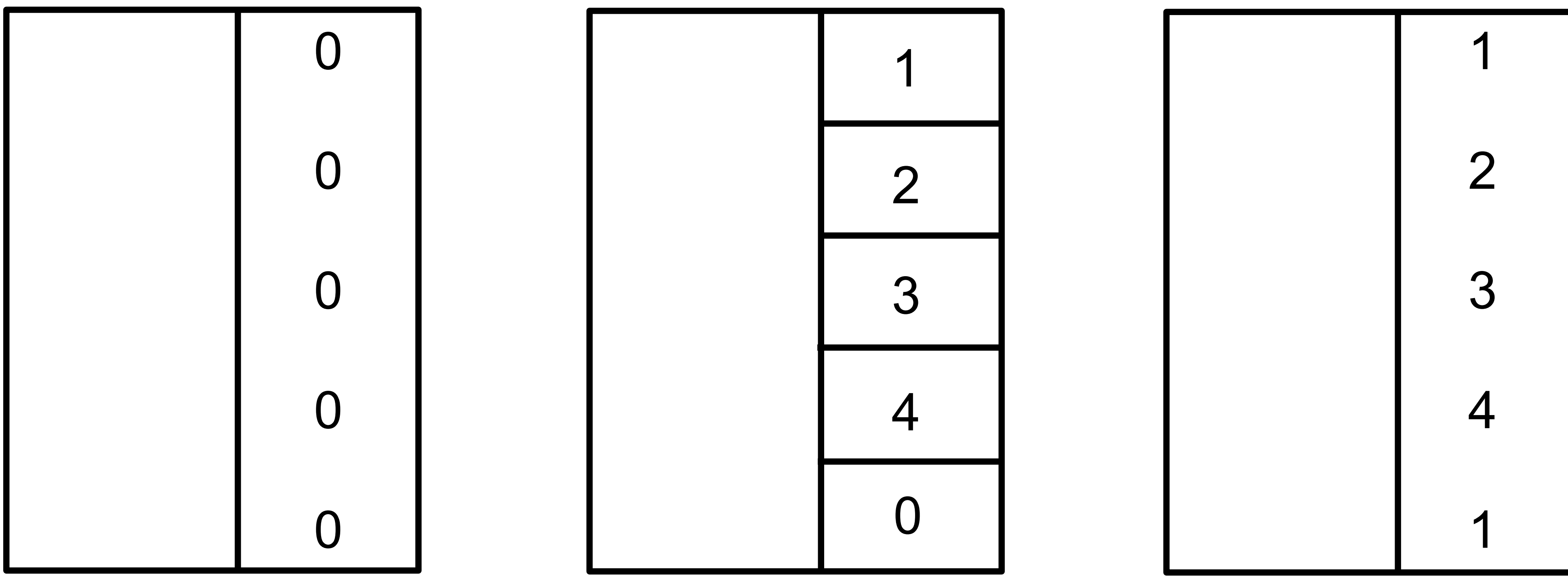


Maximum **uniformity**

Maximum **heterogeneity**

Example: k = 5

λ = 0.0 λ = 1 – 1/5 = 0.80 λ = 1.0



Maximum **uniformity** Maximum **heterogeneity**

The Edge of Chaos

http://math.hws.edu/eck/js/edge-of-chaos/CA.html

Significance of CAs for Complex Systems

- Cellular automata can produce highly complex behavior from simple rules

- Natural complex systems can be modeled using cellular-automata-like architectures

- CAs give a framework for understanding how complex dynamics can produce collective information processing in “life-like” systems

Challenges

- How can we understand computation within CAs?
- What is the meaning of “emergent computation”?
- How can we design CAs to accomplish specific desired computations?

Evolving Cellular Automata with Genetic Algorithms: A Review of Recent Work

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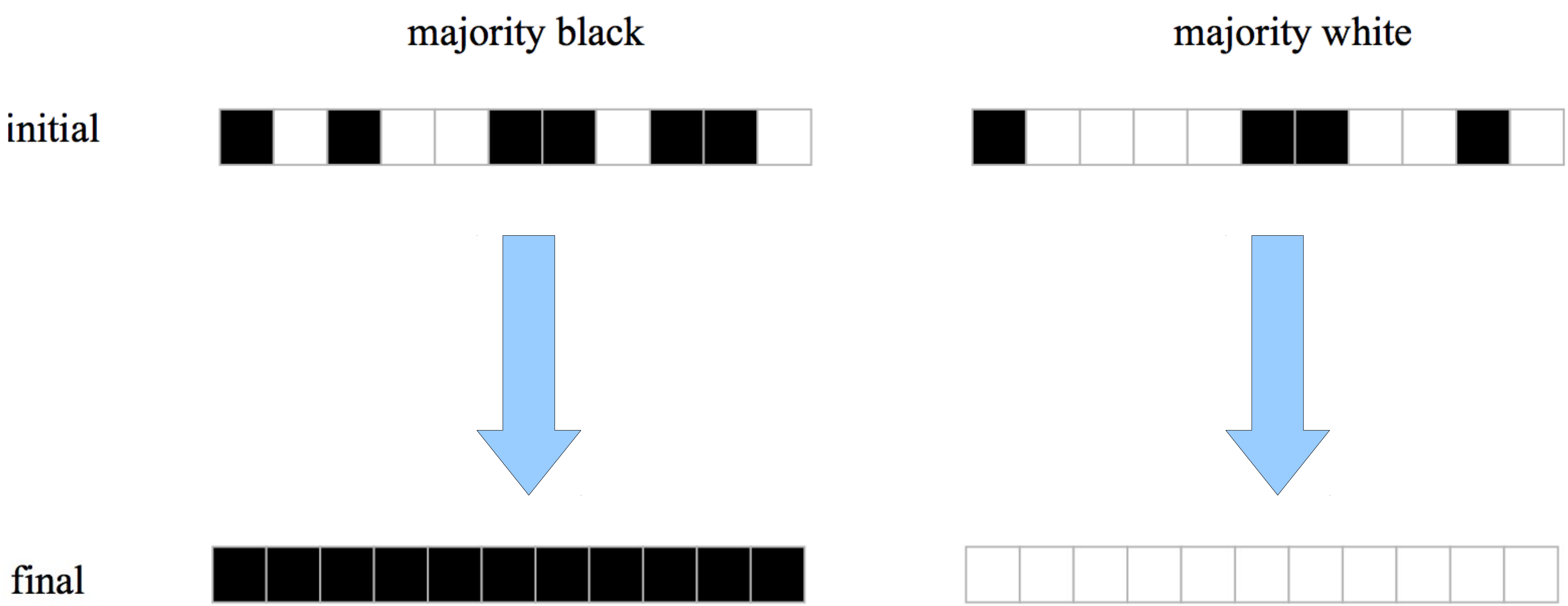
In *Proceedings of the First International Conference on Evolutionary Computation and Its Applications (EvCA'96)*. Moscow, Russia: Russian Academy of Sciences, 1996.

Task: Density-Classification

- Decide if an arbtirary initial configuration (IC) has a majority of ON cells (1) or OFF cells (0)



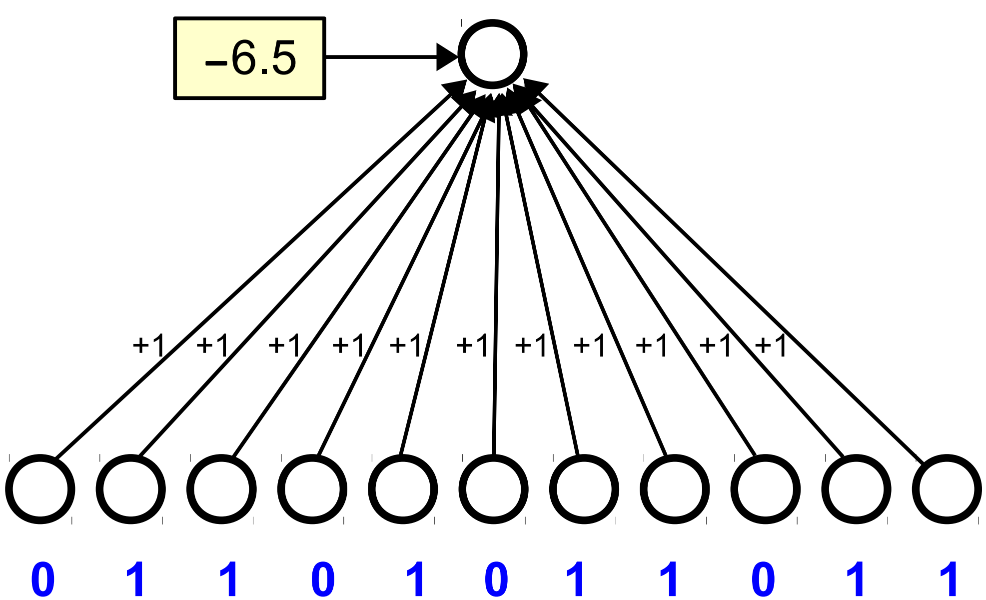
Task: Density-Classification

- Decide if an arbtirary initial configuration (IC) has a majority of ON cells (1) or OFF cells (0)

- Trivial for an ordinary computer program:
  - Maintain a counter variable *C*
  - Add 1 to *C* for each ON cell
  - Subtract 1 from *C* for each OFF cell
  - If final value of *C* > 0, then output “1”, else output “0”

Task: Density-Classification

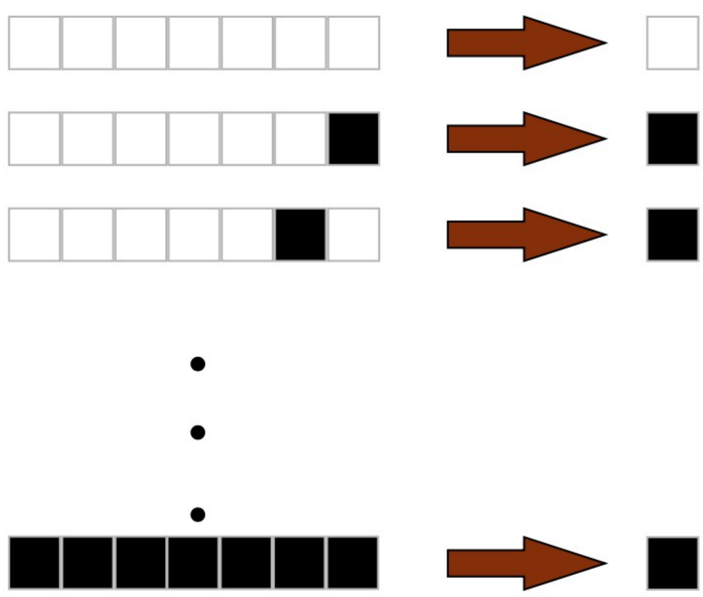
- Trivial for a neural network:
  - Set each weight to +1
  - Set bias to –N/2 where N is the number of cells



Task: Density-Classification

- Used cellular automata with a neighborhood size of 7

Rule:



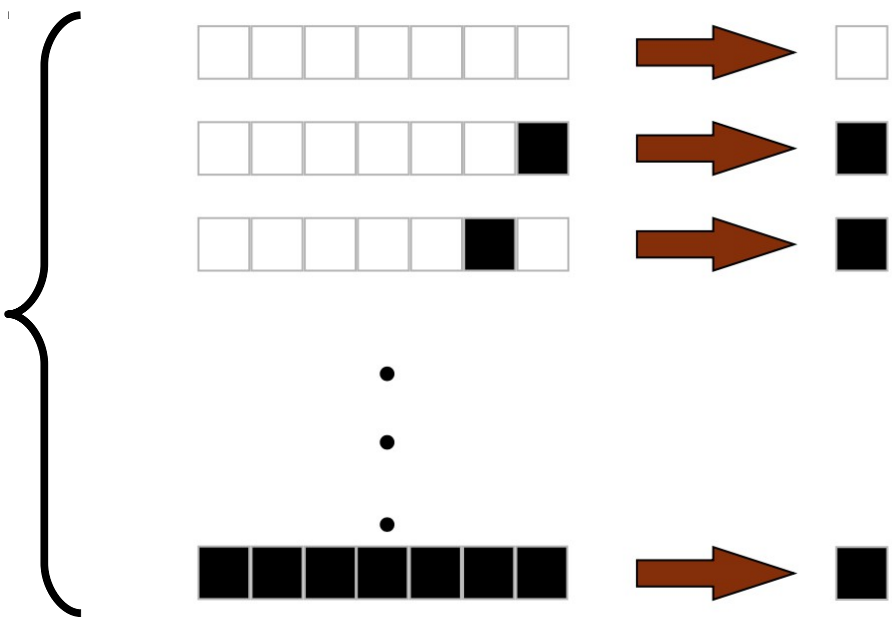
Pop Quiz

- How many neighborhoods?

$$2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 \quad = \quad 2^7 \quad = \quad 128$$

Rule:

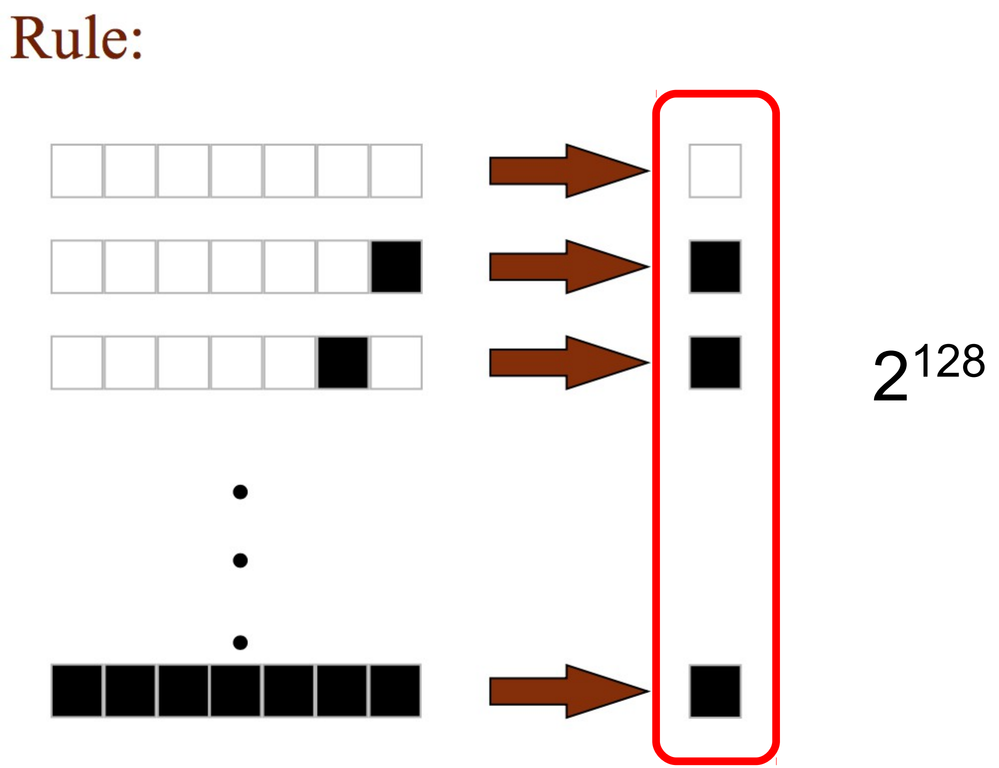
128



Pop Quiz

- How many different possible CA rules?

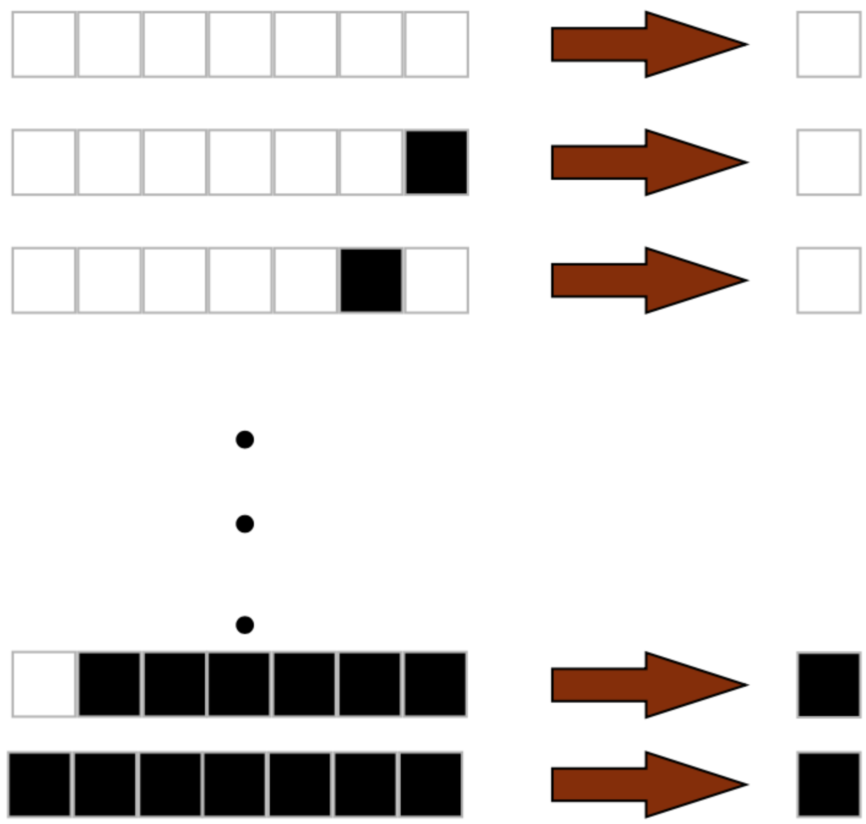
2^{128} = 340,282,366,920,938,463,463,374,607,431,768,211,456



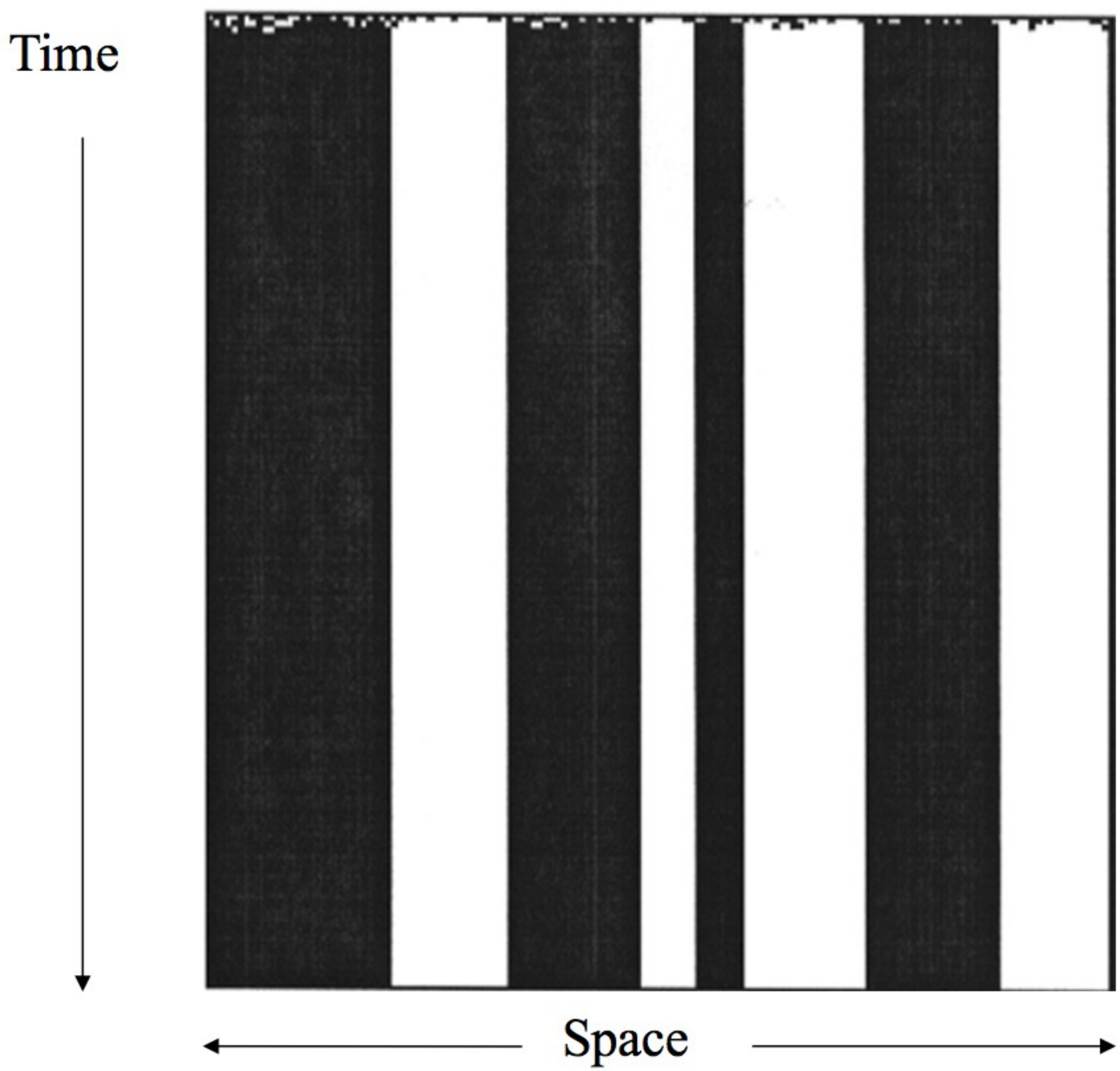
Naïve "Solution"

Majority vote in each neighborhood

Rule:



But It Doesn't Work!



A Genetic Algorithm for Evolving CAs

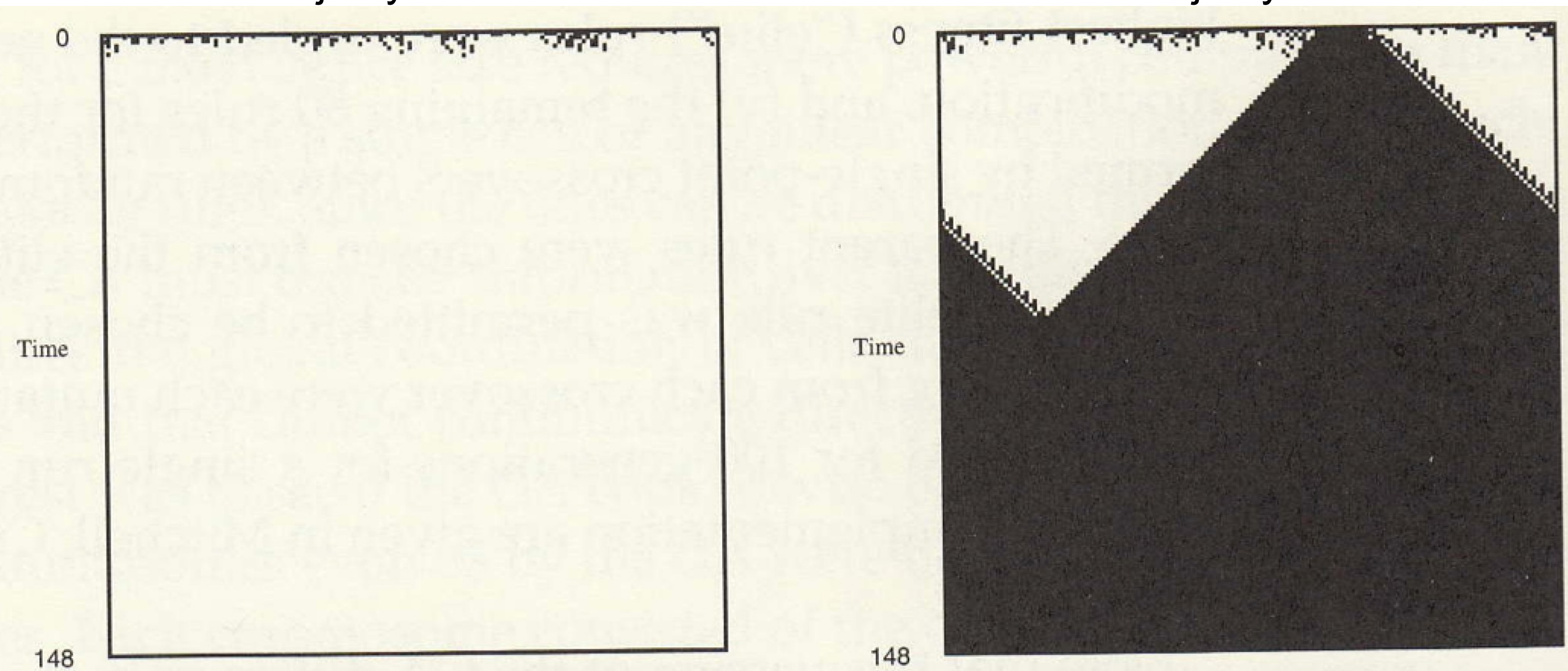
- For 100 generations:
  - Generate 100 random initial configurations (ICs), with densities evenly distributed in the range [0 … 1]
  - Calculate fitness of rules: fraction of 100 ICs that produced correct classification (all 0's or all 1's) after 2N time steps (where N = universe size)
  - Rank population by fitness
  - Copy highest 20% of the rules (the elite pool) directly into the new generation
  - Fill in the remaining 80% by randomly choosing elite rules and using single-point crossover and mutation

A Genetic Algorithm for Evolving CAs

- Elite CA rules get tested on new sets of ICs each generation
- 300 different runs of the GA were performed
- Several types of strategies evolved:
  - **Block-expansion**
    Go to all 0's unless there is a sufficiently large block of adjacent (or almost adjacent) 1's; if so, expand the block of 1's
  - **Particle-based**
    Send “signals” from one region of the Universe to another containing information about the densities of different regions

Results: Block-Expansion Strategies

Majority white Majority black



- Not very sophisticated
- All computation is "local"

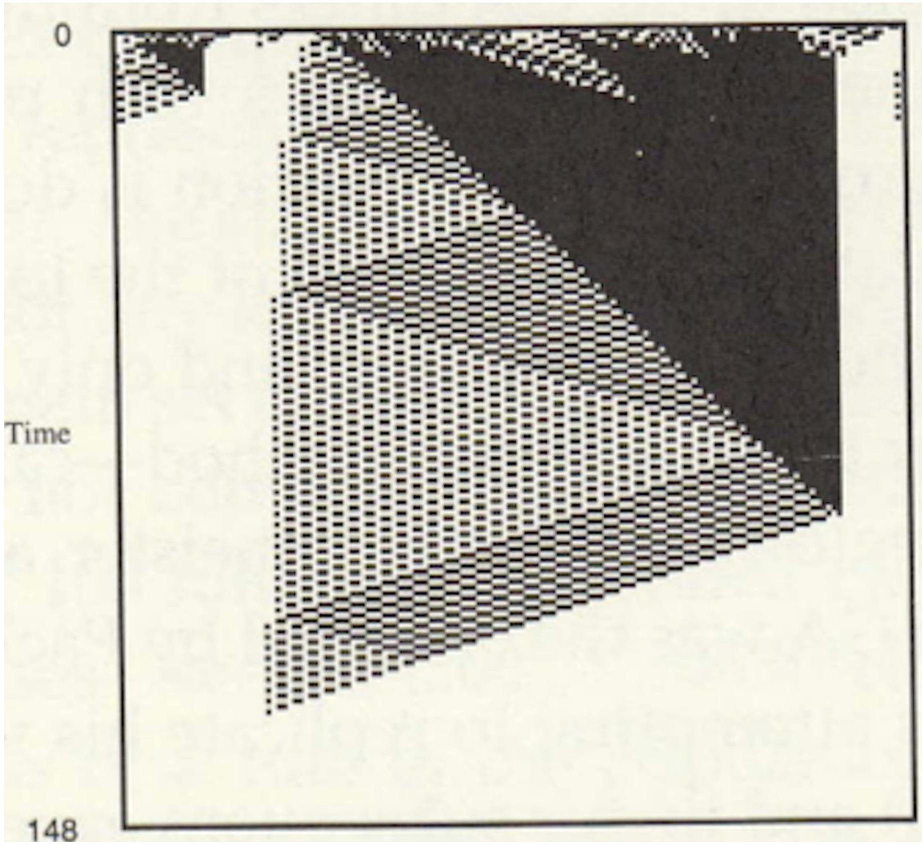
Results: Block-Expansion Strategies

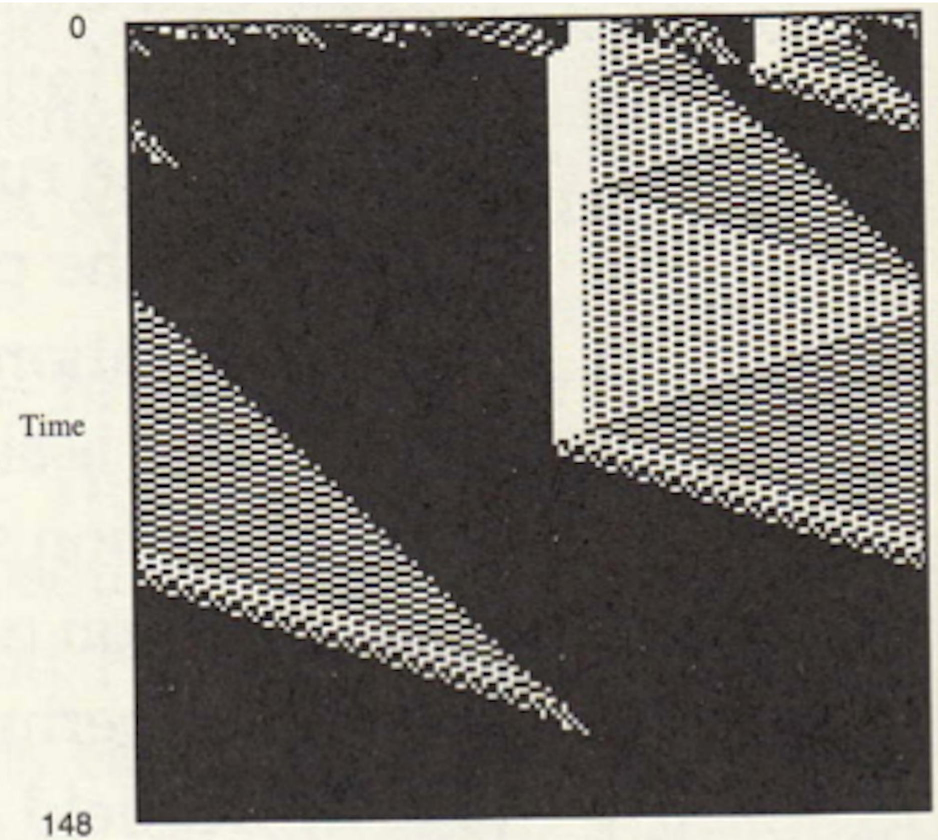
- Densities of test configurations (ICs) were evenly distributed in the range [0 … 1]
- This helped the GA make progress early on
- ...but became a problem as better CA rules evolved
- Later CA rules needed more challenging ICs with densities much closer to 0.5
- Performance on an **unbiased** sample of 10,000 test ICs degraded as the universe size (N) increased

Comparison of Strategy Performance

CA Strategy	**Fitness on a Universe of size N**		
	N=149	N=599	N=999
Majority-vote	0	0	0
Expand 1-blocks	0.652	0.515	0.503

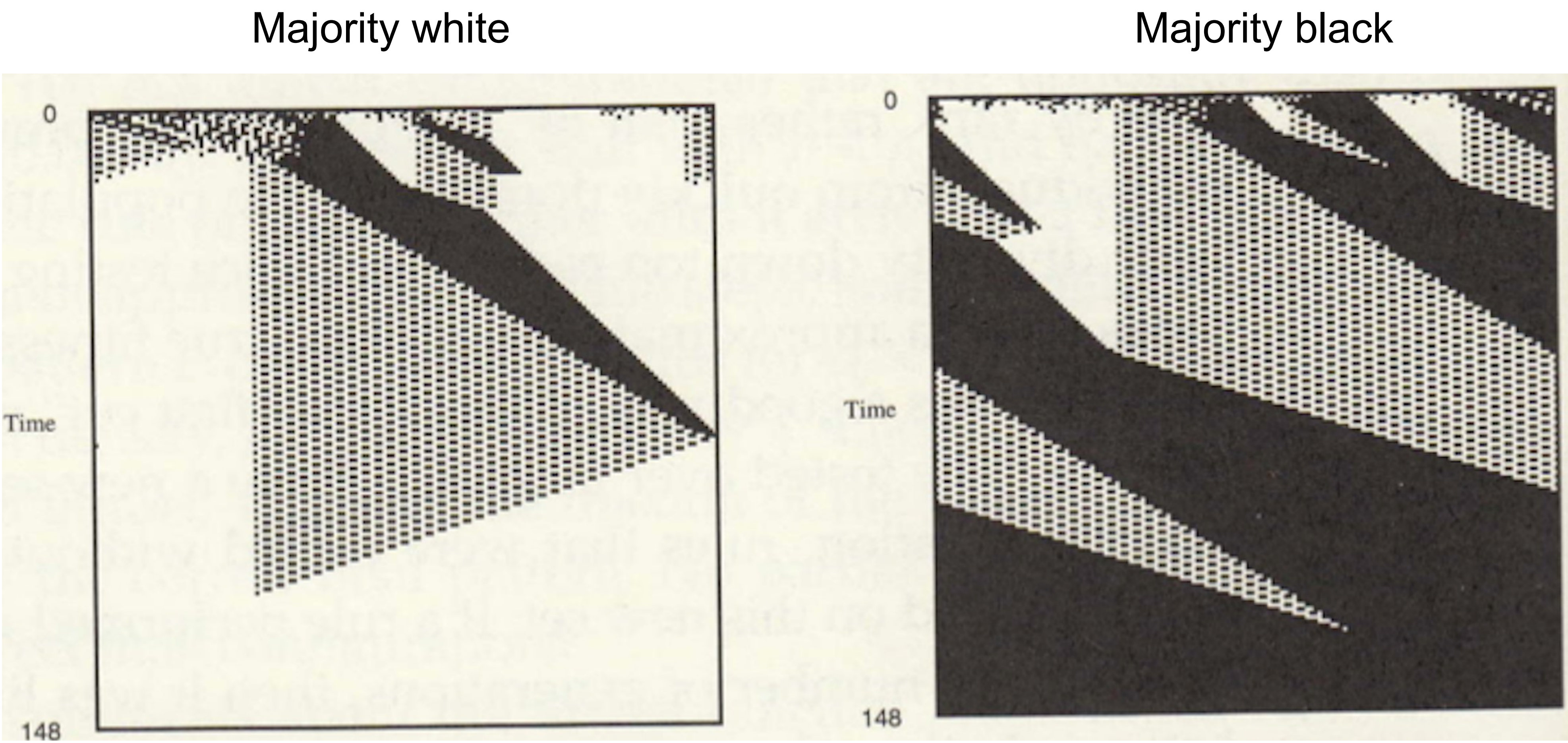
Results: Particle-Based Strategies





(b)

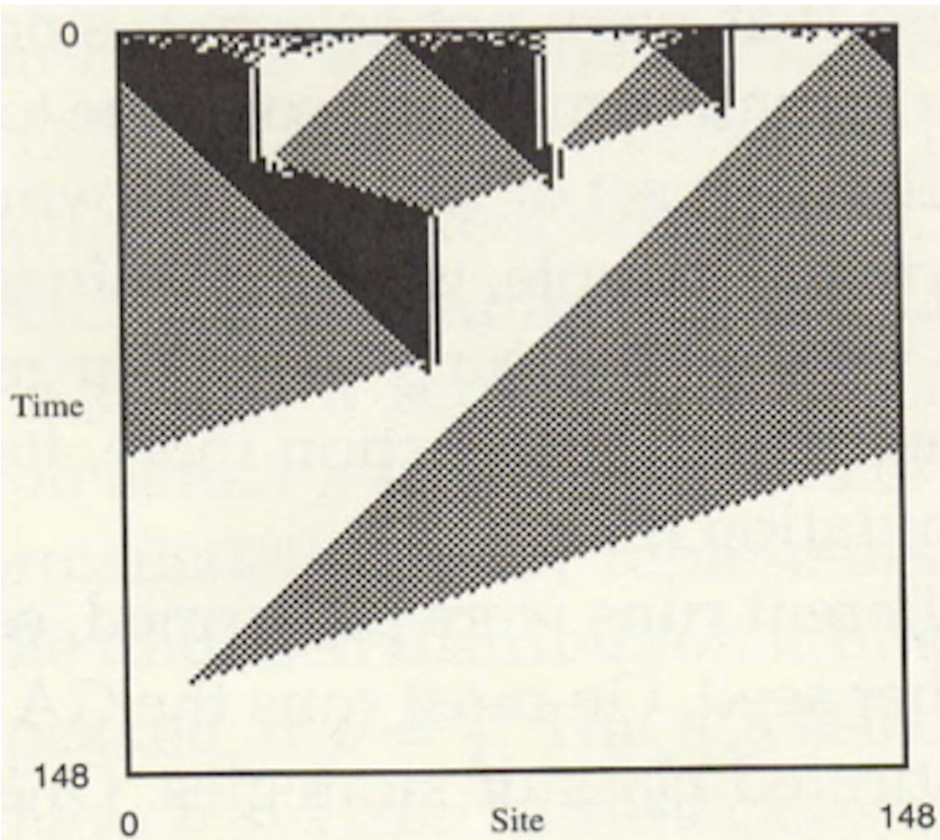
Results: Particle-Based Strategies



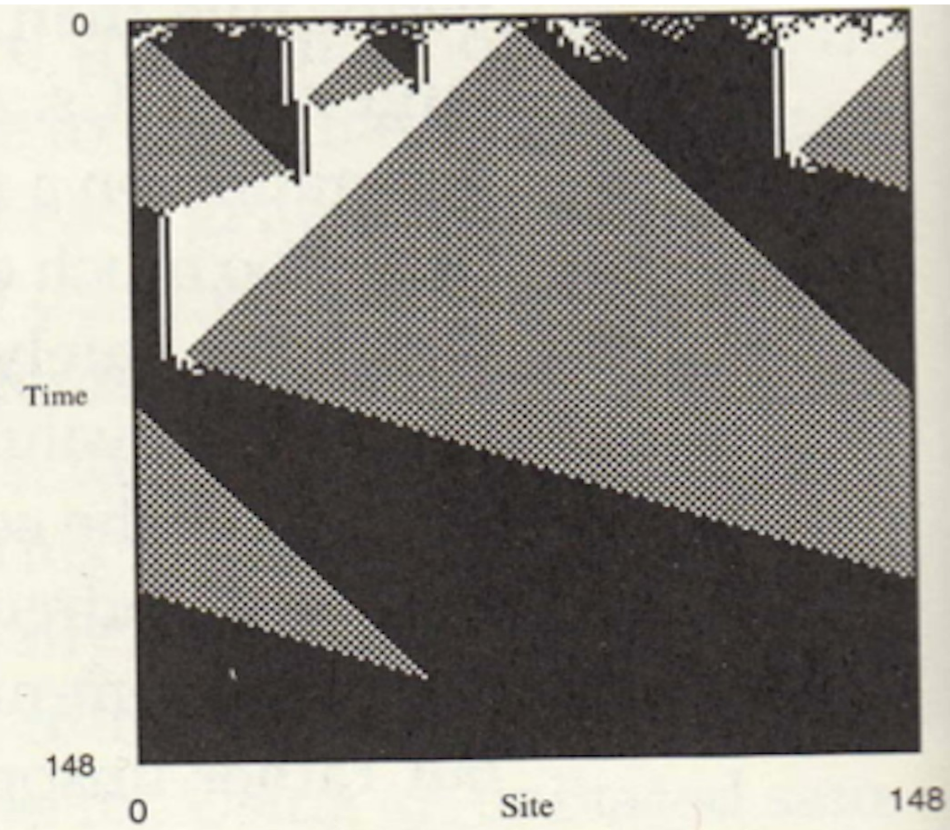
(c)

Results: Particle-Based Strategies

Majority white

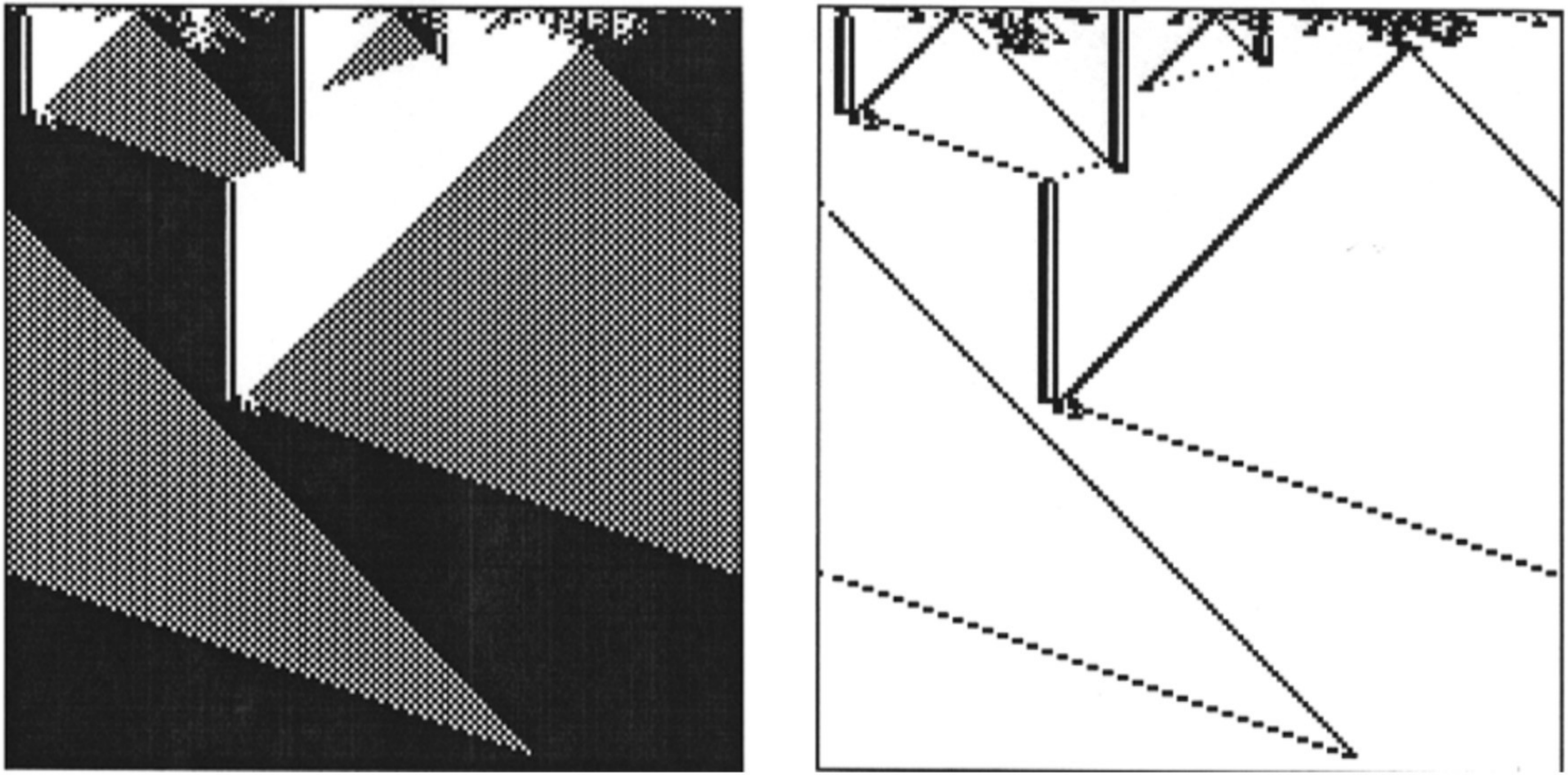


Majority black



(d)

How to Describe Information Processing?



Simple patterns filtered out

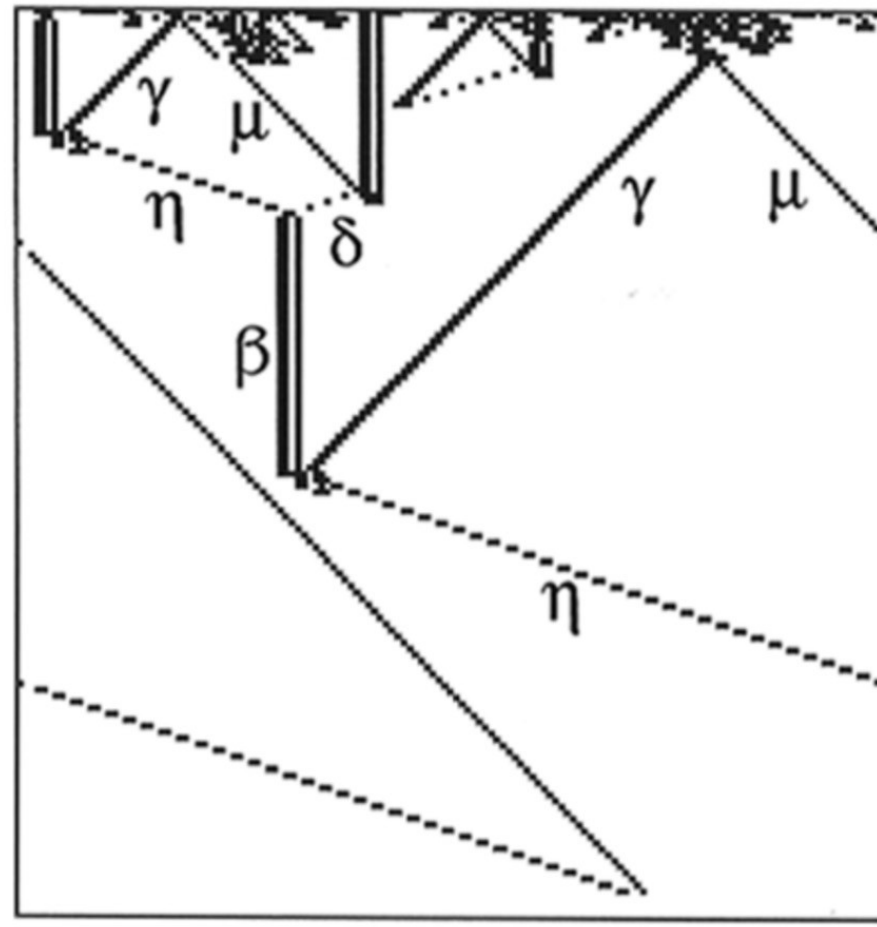
How to Describe Information Processing?

Regular Domains		
$\Lambda^0 = 0^*$	$\Lambda^1 = 1^*$	$\Lambda^2 = (01)^*$

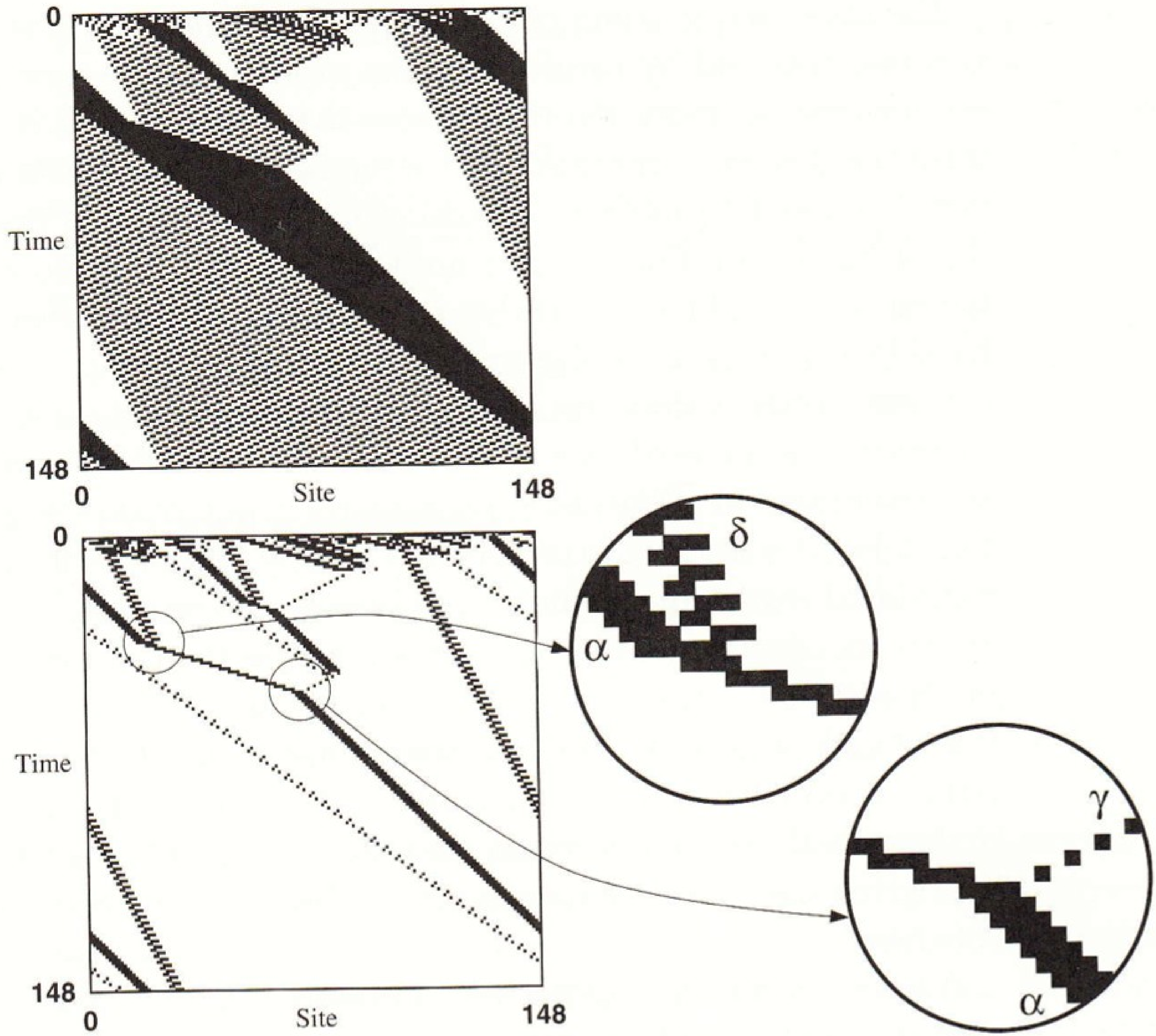
Particles (Velocities)	
$\alpha \sim \Lambda^0\Lambda^1$ (0)	$\beta \sim \Lambda^1 01 \Lambda^0$ (0)
$\gamma \sim \Lambda^0\Lambda^2$ (-1)	$\delta \sim \Lambda^2\Lambda^0$ (-3)
$\eta \sim \Lambda^1\Lambda^2$ (3)	$\mu \sim \Lambda^2\Lambda^1$ (1)

Interactions	
decay	$\alpha \to \gamma + \mu$
react	$\beta + \gamma \to \eta$, $\mu + \beta \to \delta$, $\eta + \delta \to \beta$
annihilate	$\eta + \mu \to \emptyset_1$, $\gamma + \delta \to \emptyset_0$

laws of
"particle physics"



"particles"


0
Time
148
0
Site
148
0
Time
148
0
Site
148
δ
α
γ
α

Comparison of Strategy Performance

CA Strategy	**Fitness on a Universe of size N**		
	N=149	N=599	N=999
Majority-vote	0	0	0
Expand 1-blocks	0.652	0.515	0.503
Particle-based (b)	0.697	0.580	0.522
Particle-based (c)	0.742	0.718	0.701
Particle-based (d)	0.769	0.725	0.714
Hand-designed	0.816	0.766	0.757

Better generalization than Expand-Blocks strategy

Conclusions

- GAs can (sometimes) discover CA rules that employ strategies based on coordinated information processing and communication across spatially extended distances

- The best GA-evolved rules for density classification are comparable to the best human-designed rules

- This provides a framework for studying how real evolutionary processes might give rise to complex information processing in natural systems